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Research article

Modeling residential coastal flood vulnerability using finished-floor elevations and socio-economic characteristics

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ABSTRACT

Densely populated coastal regions are vulnerable to threats associated with climate change and variability, especially storms. In the United States, millions of people are repeatedly at risk of flooding and because this number will only continue to grow, the identification of the intersection of social vulnerability and physical risk to flood inundation is essential for both coastal planning and adaptation purposes. Although a key tool to identify vulnerable populations, most vulnerability models are built at the county or coarser scales, thereby hindering the effectiveness of mitigation and adaptation planning at community scales, which are more socially and physically diverse than what county-scale analyses can reveal. We present an integrated social and physical model of vulnerability at the block-group level of geography using census data to measure social variability based population and housing data and physical exposure based on the intersection of finished floor elevation of all buildings in coastal North Carolina, USA with flood hazards maps. We identify, in a spatially-explicit manner and at multiple levels of governance, areas of high social vulnerability and their intersection with areas of high physical exposure to inundation. We found that in the 28 coastal counties of North Carolina, 45.3% of the structures within the 100-year floodplain were structurally exposed to potential damage from inundation. Supporting our hypothesized patterns of vulnerability to inundation, a significant clustering of highly vulnerable block-groups were located in Albemarle and Eastern Carolina coastal regions, yet high vulnerability outliers were also located at significant distance away from the highly physically-exposed coastline. Our findings suggest that the high-resolution block-group level analysis identified multiple levels of vulnerability to inundation at the sub-county scale and provide essential information for effective hazard mitigation within scales ranging from the community to transboundary governing bodies.

1. Introduction

The large proportion of people and property that reside in areas exposed to environmental hazards in the United States is increasingly a subject of concern (Tate et al., 2010). The recent occurrence of severe hurricanes and extensive flooding has reignited the need to understand the risk resulting from the intersection of vulnerable populations and environmental hazards (Dunning and Durden, 2011; Tate et al., 2010). The coastal zone is a core resource to many local economies and at risk from future variability in climate, increased sea-level, and intensifying tropical storms (Kettle, 2012; Nguyen et al., 2016). As a response to these concerns, coastal managers desire to understand existing vulnerabilities in order to reduce potential impacts from future hazardous events (Kettle, 2012).

The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as “the propensity or predisposition to be adversely affected” (Pachauri and Meyer, 2014; IPCC, 2014). Within the social realm, a predisposition is the result of variations occurring from inequalities in socio-economic status, ethnicity, gender, age, and education, while in the physical context, vulnerability results from varying degrees of proximity and interactions with a potential adverse event (Cutter et al., 2003; Jones and Andrey, 2007; Pricope et al., 2018). These variations often become amplified when exposed to a hazard and the impacts disproportionately fall on the more predisposed highly socially vulnerable populations (Dunning and Durden, 2011, Birkmann et al., 2013). Mitigation efforts can be taken to reduce exposure of personal property and infrastructure, but the risk of adverse effects from a potential hazard is not only dependent on proximity (Cutter and Scott, 2000). Hazards do not only interact with the physical environment, but also affect people who live in the vicinity of physically exposed environments and, oftentimes, those who are most vulnerable are at higher risk due to their social predisposition (Cutter and Scott, 2000;

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Table 1
Major characteristics of social vulnerability (Modified from Cutter et al., 2003; Cutter and Scott, 2000; and Morrow, 1999.).

Characteristic	Description of Vulnerability	Manifestation of Characteristic Leading to Increased Vulnerability
Socio-Economic Status	• Ability to absorb loss and recover • Wealth, insurance, safety nets aid in preparation and recovery	Low Income
Age Extremes	• Lack of physical ability • Restrict movement out of harm's way • Unique care requirements	Elderly, Children
Gender	• Pay discrimination • Caregiver responsibilities • Gender specific employment opportunities	Female
Ethnicity	• Cultural language barriers • Limited family networks • Minority discrimination	Non-White
Family Structure	• Number of dependents • Increased financial burden • Care responsibilities	Dependents, Single-Parent Households, Family size
Renters	• Lack of Financial Stability • Transient Population	Renters, Rental Units
Special Needs	• Institutionalized (correctional, nursing, mental care facilities) • Supervised care • Group-quarters (military bases, universities, juvenile institutions)	People with Special Needs, people in group quarters, people in an institution
Total Population	• Complicate evacuation • Strain on resources • Economic dependence on agriculture and farming	Urban and rural Population,

Jones and Andrey, 2007; Tate et al., 2010). This interaction became evident in the impacts from Hurricane Katrina, where, while the overall evacuation was considered successful, over 250,000 people were unable to flee New Orleans due to lack of access to resources resulting from social inequalities (Cutter et al., 2006; Schmidtlein et al., 2008). The latest (Fourth) National Climate Change Assessment report highlights the US Southeast coastal locations as being one of the most at risk regions from flooding given a doubling of days with extreme precipitation since the 1980s (Carter et al., 2018). The recent Hurricane Florence that affected much of coastal and even larger swaths of inland North Carolina further proves that point and calls for urgent assessments that can help municipalities, counties and larger governing bodies more effectively plan for and map the course for recovery efforts from storm and flooding-related disasters.

Vulnerability is a multidimensional concept and it is extremely difficult to identify direct observable measures to quantify population risk to a potential environmental hazard (Jones and Andrey, 2007; Schmidtlein et al., 2008; Tate, 2012). Vulnerability modeling and assessments have emerged as a possible solution to this problem and have been utilized in a wide-range of disciplines to examine the interactions of various environmental, social, institutional, and or political systems and their impacts on populations (Peduzzi et al., 2009; Zakour and Gillespie, 2013; Giupponi and Biscaro, 2015; Mainali and Pricope, 2017). Rarely do environmental hazard studies combine the examination of the components that create physical and social vulnerabilities together and even more rarely do they do so in spatially explicit ways at the highest resolution afforded by empirical observations (Mainali and Pricope, 2018). Most studies primarily focus on either variations in social inequalities and or physical vulnerabilities modeled for future conditions verified by past events, potentially missing the combined effects on the overall vulnerability, which provides a more complete measure of pre and post hazard impacts (Tate, 2012; Tate et al., 2010; Viavattene et al., 2018).

Another overall limitation of vulnerability and risk studies is the scale of analysis. Many studies present the results at the county scale to replicate and compare to other parts of the country, but the exclusion of sub-county data in an assessment can result in assumptions and generalizations (Cutter et al., 2003). These generalizations can limit the usefulness of the data for mitigation planning within smaller units of governance due to the potentially different vulnerability within individual counties that is lost at lower resolutions of analysis (Frazier et al., 2014). The few studies that have examined vulnerability at a sub-county scale (tract or block-group) have limited the scope of their research to studying the varying influences of indicators at the sub-county level for a single county (Frazier et al., 2014; Wu et al., 2002). Higher spatial resolution data used in vulnerability studies better illustrate place-specific characteristics that larger county-level data cannot (Cutter et al., 2003; Frazier et al., 2014). By expanding the examination of sub-county vulnerability to a regional level, a complete assessment can be made thus having a more significant potential to contribute to enhancing mitigation strategies and long-term planning (Cutter, 1996; Frazier et al., 2014; Schmidtlein et al., 2008).

1.1. Social vulnerability

The understanding of where populations predisposed to risks exist can influence future mitigation efforts and can change the potential impact a hazard has on society (Schmidtlein et al., 2008; Balica et al., 2012). Social vulnerabilities result from inequalities in socio-economic status, ethnicity, gender, age, and education (Cutter et al., 2003; Jones and Andrey, 2007; Pricope et al., 2018). Across any geographic context, from a small community to across an entire county, different groups of people and households exist, and the concentration of those predisposed groups tend to increase the vulnerability of an area (Morrow, 1999). Home ownership and renter occupied housing indicate financial stability of an individual or household (Morrow, 1999). Those who rent often do so because of the lack of funds to purchase a home or are transient to the area, leaving them vulnerable to insufficient funds and options for shelter in preparation for an adverse event (Cutter et al., 2003; Morrow, 1999). Individuals displaying age extremes, such as the elderly, are more likely to lack the physical strength to prepare and may be reluctant to evacuate before a hazardous event (Cutter et al., 2003; Morrow, 1999). While these are only a few examples of social characteristics, it is important to remember that these often occur in combination (Table 1). When already predisposed ethnically diverse communities with multi-generational families try to evacuate within a concentrated urban area, the combined effects result in the amplification of vulnerabilities and increase the exposure to a hazardous event (Morrow, 1999).

The construction of an index that quantifies the social characteristics that contribute to vulnerability to a hazardous event has been tackled across geographic, political and ecological disciplinary practices (Gerlitz et al., 2017; Pricope et al., 2018). One methodology to achieve this is the Social Vulnerability Index (SoVI), created by Cutter

and Scott (2000) to generate a comparable measure of social vulnerability across the U.S. at the county-level of geography (Dunning and Durden, 2011). This framework was initially designed to analyze the social characteristics to identify vulnerability to a wide range of potential hazards (Cutter et al., 2003; Dunning and Durden, 2011). Since its construction, SoVI has been subjected to sensitivity analyses to assess changes introduced by scale and relative robustness to comparable index designs for validation (Schmidtlein et al., 2008; Tate, 2012). It has also been applied, in a limited extent, at a sub-county scale to identify the social variations that exist at a more local level and has guided the development of integrated measures of vulnerability to a wide range of environmental hazards (Boruff et al., 2005; Dunning and Durden, 2013; Hardy and Hauer, 2018; Tate et al., 2010). The SoVI framework has undergone many changes to the selection of key variables since its inception, with differences attributed to data availability and developments in the understanding of vulnerability drivers (Hardy and Hauer, 2018). The selection of model variables, whether social or physical, largely depends on the characteristics that render a community most susceptible to loss and their ability to recover from and respond to a wide range of potential hazards (Cutter, 1996; Schmidtlein et al., 2008). Due to a lack of an agreement upon a consistent set of empirically defined, readily available representative variables, we choose to not limit this study to subjective decisions about the inclusion of social variables in the vulnerability index construction (Jones and Andrey, 2007; Tate, 2012). Instead, we included all available socio-economic variables and then used statistical analyses to identify the statistically significant factors for our study area. In this approach, the important socio-economic variables are derived for the study area rather than previous research dictating the key variables of importance.

1.2. Physical vulnerability

In 1999, Hurricane Floyd brought record flooding to North Carolina, adding more precipitation to the area hit by Hurricane Dennis weeks prior and exceeding the 500-year floodplain. This storm damaged 80,000 homes with a payout of $182 million from Federal Emergency Management Agency (FEMA) in insurance claims alone, covering only 13% of those affected by flooding (National Weather Service, 2018a). More recently, in 2016, Hurricane Matthew resulted in many of the inland areas and rivers rising to crests higher than records set during Floyd and was recorded as the second major flooding event to hit North Carolina within the last two decades (National Weather Service, 2018b). Periodic events such as nuisance flooding, high astronomical tides, precipitation, and varying intensity-tropical storm events that frequent the Carolina coastline pose a threat to communities and complicate coastal and floodplain management (Geoghegan et al., 2018), as evidenced most recently by the effects of Hurricane Florence in 2018.

In 2000, as a response to Hurricane Floyd, the State of North Carolina Floodplain Mapping Program in partnership with FEMA began to modernize its floodplain mapping program to make digital formats more readily accessible to municipalities and the public to assess the risk and potentially lessen future loss from flooding (NCFM, 2008). The concept of risk, within the realm of environmental and natural hazards, implies a chance of a particular outcome occurring (Hufschmidt, 2011) and thus flood hazard maps that identify zones at risk to predicted base flood elevations (BFE) from only the 100-year and 500-year flood events are provided. The outline of the 100-year flood zone identifies the areas that have 1 in 100, or 1%, chance of inundation occurring in a given year. Similarly, a 500-year flood zone has 1 in 500, or 0.2% chance of occurring (USGS, 2016). The location of properties within these boundaries is used to determine insurance rates and building requirements including the mandated height for a structure's finished-floor elevation (FFE) (NCFM, 2008).

Beginning in 2009, the North Carolina Floodplain Mapping Program has also conducted a building inventory containing the FFE for all structures in North Carolina. This high-resolution statewide dataset, which only exists in North Carolina to our knowledge, provides the opportunity for a spatially explicit analysis of structure vulnerability to predicted BFE. Various mitigation strategies exist to limit vulnerability associated with inundation, such as raising roads, building dikes, and flood-proofing structures (Aerts et al., 2008). The raising of a structure has been found to be an effective preventative measure to reduce exposure to flooding, but costs associated with raising a structure are significant, thus making this an investment that is not available to all socio-economic classes (Botzen et al., 2013). By utilizing the BFE for the 100-year floodplains and the FFE for each residential structure, an assessment of a physical vulnerability to inundation can be determined.

With access to the recently available, unprecedented, and unique to North Carolina high-resolution building inventory dataset containing FFEs and other variables for all structures in NC, this study analyzed the intersection of social and physical vulnerability in the 28 coastal counties of NC and summarized these at the block-group level of geography. We propose a spatially refined model of vulnerability to coastal inundation that builds on the SoVI approach to quantify variations in socio-demographic characteristics and exposure to flooding using FFEs within the 100-year flood zone. The primary research question we addressed, with direct applicability to coastal planning and management, was whether a composite index developed at higher spatial resolution provides additional insight into the spatial distribution of population vulnerability to flood inundation in a low-lying coastal location. Secondarily, we aimed to identify which counties and regional government units (Council of Governments, in this case) have the most significant number of vulnerable populations and have the highest percentage of block-groups at risk of flooding. Third, we explored how the exposure to flood risk and the social vulnerability of populations shifted in space when they were combined. We hypothesized that the highest levels of vulnerability to inundation were concentrated in the areas of high exposure along the coast of North Carolina.

2. Methods

2.1. Study area

Bordered by the Atlantic Ocean to the east and the Appalachian Mountains to the west, North Carolina is the ninth most populous state in the U.S. with an area of 48,617 square miles (United States Census Bureau, 2017a, 2017b). Based on 2017 estimates, North Carolina has approximately 10 million people and a poverty rate of 15.4% which is 2.7% higher than the national average of 12.7% (United States Census Bureau, 2017a, 2017b). There are over 4.5 million households in North Carolina and approximately 900,000 of them reside in the coastal plain region (United States Census Bureau, 2017b). The NC coastal plain covers 45% of the total state's area and is dominated by rural agriculture, small towns, coastal communities, and a few larger cities (Bobyarchick and Diemer, 2005; Street et al., 2007). North Carolina contains 3375 miles of coastal shoreline, dominated by wetlands, and gently slopes inland to the hilly Piedmont region (Bobyarchick and Diemer, 2005). The humid subtropical climate and extensive coastline make this region attractive for urban development driven by seasonal vacationers and retirees who seek to move to a milder climate.

The study area consists of 28 North Carolina counties that fall within four regional Councils of Governments (COGs) with coastal characteristics. COGs are transboundary governance bodies that represent local governments at the state-level and provide support for regional planning (Fig. 1). The COGs function as the main pipeline of information from the state and federal agencies for many rural communities that may lack funding to support environmental resource and planning departments (N.C.A.R.C.O.G, 2017). The total population of the coastal region is approximately 1.5 million people, with the largest population of 633,028 people residing in the Eastern COG in cities such as Goldsboro, Jacksonville, and New Bern (Fig. 2). The higher

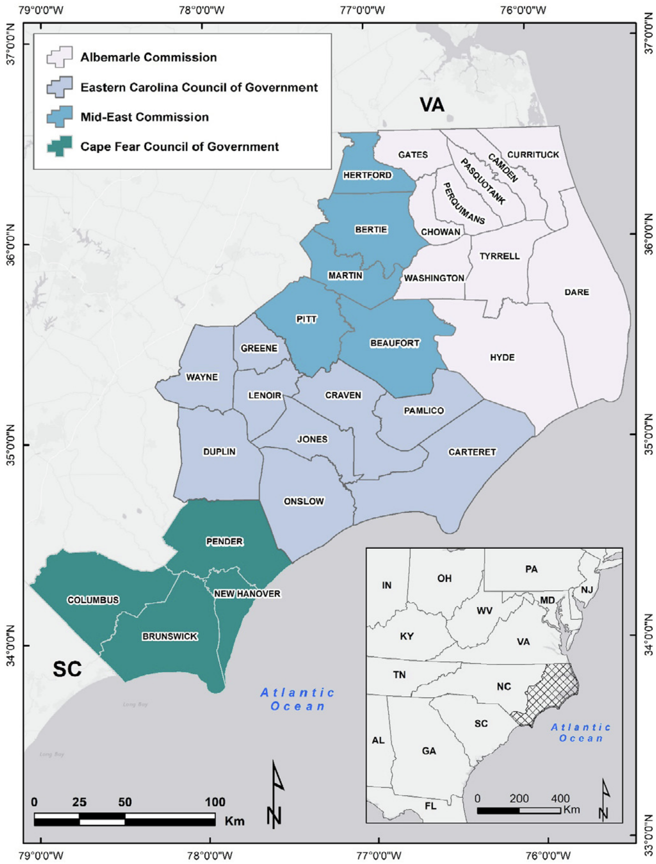

Fig. 1. The four coastal North Carolina Councils of Governments comprised of 28 counties.

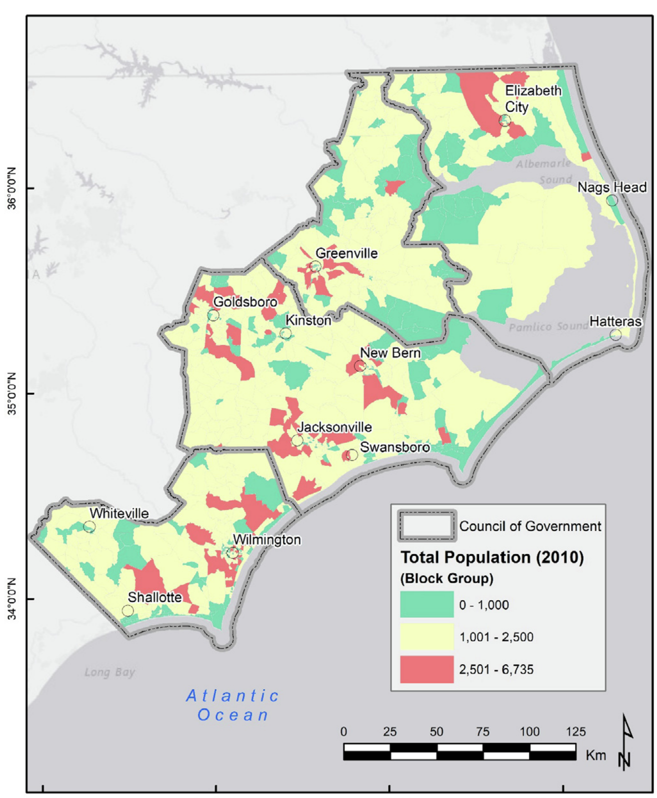

Fig. 2. The 2010 total population by Census block-group for coastal North Carolina, USA.

populated places are in the southern coastal plain with the City of Wilmington (New Hanover County) at over 200,000 people and conversely, the northern coastal plain is much less populated, with the Albemarle COG having the smallest population (171,996 people) (Table 2).

2.2. Data sources

2.2.1. United States Census 2010

The decennial census program, administered by the US Census Bureau since 1790, has enabled researchers to study current conditions and track changes through time. Census information, gathered at a variety of geographical scales, is used to guide policy formation and the identification of communities requiring assistance throughout the United States (US Census Bureau, 2017a). Last distributed in 2010, it collects detailed information tables for demographic, housing, social, and economic information for the population. These data are available for free from the American FactFinder website (factfinder.census.gov), where the user queries for tables at the selected spatial scale. Census geography, TIGER/Line files, are also available from the US Census Bureau website (https://www.census.gov/geography.html). The various geographic units used for population enumeration are created to attempt to achieve areas of similar population characteristic (Frazier et al., 2013). The smallest geographic unit is a block and follows existing infrastructure such as roads, railroads, trails, etc. The block-group is an aggregated set of adjacent blocks and is the highest resolution of geography for the 2010 decennial census that also includes the largest amount of attribute data. Block-groups have between 600 and 3000 people. At the block-group level a total of 228 tables (population and housing) were downloaded and compiled for the 28-county study area at the block-group level of geography.

2.2.2. National Flood Hazard Layer (NFHL)

In 1968, the National Flood Insurance Program (NFIP) was established to provide insurance to those affected by flooding throughout the United States. The Federal Emergency Management Agency (FEMA) manages this federally funded program, and through a partnership with each state, the NFIP receives updated maps from the state agencies. The State of North Carolina provides the most recent digital maps to the public via the Flood Risk Information System (NC FRIS) (fris.nc.gov) (NCFM, 2008). Flood hazard maps (in shapefile format) are available for download for each county from either the NC FRIS website or any county in the United States can be downloaded from the National Flood Hazard Layer (NFHL) website (https://www.fema.gov/national-flood-hazard-layer-nfhl). These maps contain floodplain zones and BFE attributes in feet above mean sea-level that were established through studies that model water elevations under various flood frequencies (NCFM, 2008).

2.2.3. Building inventory finished floor elevation (FFE)

The availability of National Flood Hazard Layer digital floodplain maps, used to determine insurance rates and building requirements, provides the public with information to analyze risk to a potential flood event. Building codes for coastal regions require new construction be built above the BFE and meet both minimum federal requirements and local ordinances for FFE. Building code requirements change over time and this results in older structures that were built before the current flood map BFE's typically not meeting the current elevation requirements, and possibly being exposed to damage from future flood inundation.

FFE is defined as the lowest elevation of the enclosed area of a structure, above grade, used for any purpose other than parking, building access, or storage (FEMA US Department of Homeland Security, 2017). The State of North Carolina conducted field measurements to the bottom of the front door for all structures within the 100-year floodplain and used elevation certificates for all the structures

Table 2
The 2010 US Decennial Census number of block-groups and population summarized by regional council of government and county.

Region	Number of Block-Groups	Population	Region	Number of Block-Groups	Population
Eastern Carolina Council of Government	416	633,028	Albemarle Commission	121	171,996
Carteret County	69	66,469	Camden County	5	9980
Craven County	64	103,505	Chowan County	12	14,793
Duplin County	34	58,505	Currituck County	13	23,547
Greene County	13	21,362	Dare County	24	33,920
Jones County	7	10,153	Gates County	10	12,197
Lenoir County	47	59,495	Hyde County	4	5810
Onslow County	95	177,772	Pasquotank County	25	40,661
Pamlico County	12	13,144	Perquimans County	10	13,453
Wayne County	75	122,623	Tyrrell County	4	4407
			Washington County	14	13,228
Cape Fear Council of Government	**286**	**420,413**	**Mid-East Commission**	**190**	**286,363**
Brunswick County	89	107,431	Beaufort County	35	47,759
Columbus County	47	58,098	Bertie County	19	21,282
New Hanover County	119	202,667	Hertford County	19	24,669
Pender County	31	52,217	Martin County	21	24,505
			Pitt County	96	168,148

outside of this area to create a dataset (in shapefile format) that contains the polygon extent of each building in the state. The resulting shapefile contains attribute information for every building including building value, characteristics, and collection method. The centralization of this information into a statewide database provides coastal managers and planners with a unique opportunity to use this information to evaluate the current exposure of the housing, commercial and other built infrastructure and the possibility to assess future storm loss due to damage from flood inundation. Using this dataset, we calculated that there are approximately 900,000 buildings in the coastal plain region of NC (represented by the 28 coastal counties and four COGs in our study area. Fig. 1), of which 158,194 are located in the state's most vulnerable 100-year floodplain.

2.3. Analytical techniques

2.3.1. Social vulnerability

All statistical processing was completed in SAS, a statistical analysis software, and the results were exported to Microsoft Excel for analysis and formatting prior to importing into Esri ArcGIS 10.5x software for visualization and spatial transformations. For assessing social vulnerability, the population and housing data tables from the 2010 decennial census represent many of the social circumstances that characterize an exposed population (Jones and Andrey, 2007). Each data table contained a variable of total (people or households) sampled for each census subject and subsequent sub-total variables for the various topics of each subject (e.g. race, household type, age, etc.). The Census contains a wide range of sub-total variables; therefore, the same level of fields was used from each data table. We retained the first set of topic sub-totals and the subject total for each of the 228 data tables. Those variables that were not already aggregated to averages or summarized as median values were normalized to percent population for the block-group (Dunning and Durden, 2013; United States Census Bureau, 2012). The resulting set was tested for multicollinearity, and if found to be correlated ($r = 1.00$), the most representative variable was used in the analysis. The census variables were measured at several measurement scales (e.g. percent population, average, and median) and were standardized before the statistical analysis (Cutter et al., 2003; Dunning and Durden, 2013; Jones and Andrey, 2007).

$$Z\text{-}\ \text{score} = (x - \mu)/\sigma \tag{1}$$

Using Equation (1) a standard z-score was created, where x is the observation value, μ is the mean of all the observations, and σ is the standard deviation. The z-score converts the variables to a scaled representative value with a mean of zero and a standard deviation of one.

Principal Component Analysis (PCA) is commonly used to reduce a large collection of variables to a representative set of core components (Joliffe amd Morgan, 1992; Jones and Andrey, 2007). PCA also functions as a non-subjective reductionist technique, with the components determined based on the proportion of variance in the population explained by the original dataset (Jones and Andrey, 2007). A varimax rotation was applied to reduce the tendency of any variable from loading too highly on a single component (Cutter et al., 2003). Component extraction utilized the Kaiser Criterion, eigenvalue greater than 1, and visual analysis of the eigenvalues in a scree plot identified where the contribution of each additional component begins to level off. The most significant components were assigned names for the social component by identifying the variables that loaded significantly. Each of the components were then interpreted for cardinality. This was done to ensure that the resulting block-group loading correctly increased or decreased the influence on the final index based on the correlation with the key vulnerability concepts. After the cardinality was assigned, each of the social components were used in a weighted sum model where the percent variance explained was used to compute a social index score for each block-group (Schmidtlein et al., 2008). Lastly, the social vulnerability resulting from the weighted additive model was subsequently normalized using the calculation of z-scores (Equation (1)).

2.3.2. Physical vulnerability

The North Carolina building inventory (5,223,879 polygons) contains the locations of all building footprints in North Carolina. Those falling within the study area (approximately 900,000 polygons) had, among other fields, an attribute for the flood zone category and the FFE.

BFE is calculated for flood hazard areas that are subject to 1% annual chance of flooding (100-year floodplain). To identify the BFE, the flood hazard maps (in shapefile format) for each county were merged into a single flood hazard feature class and spatially joined to the building footprints. However, occasionally a single building polygon could intersect more than one floodplain zone where there are two different BFE attributes. It was decided that it is preferable to use the greater BFE value in order to identify any possible structures at risk and, therefore, for those buildings with more than one BFE value, a summarization was calculated on the unique Building ID and the maximum BFE value was then joined back to the building feature class. The result was a single maximum BFE value for every structure within the 100-year floodplain (128,441 buildings in our study area).

To determine if a building is exposed to potential damage using the modeled BFE, the BFE was subtracted from the FFE. Any materials built into the subfloor (e.g. insulation, duct work, and or electrical) of a structure will begin to experience damage from inundation when the flood waters reach one foot below the FFE (Rogers et al., 2011). Therefore, if the difference between FFE and BFE is less than one foot

then the building was identified as being potentially at risk to flood inundation.

The proportion of buildings with the FFE minus BFE difference below one foot was calculated for each block-group. Within the study area, a block-group may intersect more than one flood zone; however, for this study, we were interested in the 100-year flood zone because it represents the areas of greatest exposure. An intersection was performed to determine the percentage of 100-year flood zone within each block-group. When a large proportion of a block-group intersects 100-year flood zone, there is an increased exposure to potential inundation. The percentage of buildings potentially flooded and the proportion of the block-group within the 100-year flood zone was summed in an equal weights additive model resulting in a total exposure to inundation. Lastly, the total exposure was normalized using the calculation of z-scores (Eq. (1)) resulting in a final exposure.

2.3.3. Vulnerability to inundation composite index

The block group vulnerability to inundation was assessed by creating a categorical intersection of the final physical and social vulnerability index scores in a matrix of low, medium, and high classes across both categories we computed (social and physical). The intersection of the two indices identified where block groups were both high physical vulnerability and high social vulnerability resulting in an overall high vulnerability to inundation.

2.3.4. Mapping geographic patterns

To visualize the spatial distribution and quantify geographic patterns using spatial statistics, the three final standardized index values (social, physical and combined vulnerability index) were joined to the block-group polygons. To visually compare the indices, a standard deviation class break method was used to break up the indices into three classes indicating high, medium and low vulnerability for each (Schmidtlein et al., 2008). Those block-groups with greater than +0.5 standard deviations index value indicated high vulnerability, +0.5 to −0.5 standard deviations indicated medium vulnerability, and less than −0.5 standard deviations identified areas of low vulnerability (Cutter and Finch, 2008; Schmidtlein et al., 2008).

To determine if the spatial distribution of the vulnerability index was the result of random chance, a spatial autocorrelation was performed at the local and regional distance thresholds that were previously identified using the Ripley's K statistic (Ord and Getis, 1995). A cluster and an outlier analysis were subsequently calculated using the Anselin Local Moran's I test at the local and regional distance band thresholds to identify statistically significant areas of clustering and outliers for high and low index values so as to identify patterns of areas of similarity in vulnerability (Cutter and Finch, 2008). All data resulting from these analyses was then further interpreted statistically in the Statistical Analysis Software (SAS).

3. Results

3.1. Social vulnerability

The results of the PCA were analyzed using the Kaiser Criterion and eigenvalue scree distribution and yielded a total of 12 major components that explained 56% of the variation across the study area (Table 3). The first component explained 14.15% of the variance and was associated with family structure: white head-of-household and large household size with more than four children (Fig. 3A). The second component explained 9.84% of the variance and was related to population size (total population and total housing units) (Fig. 3B). The third component explained 6.32% of the variance and is “some other race” which is not one of these: White, Black or African American, American Indian and Alaska Native, or Native Hawaiian and Other Pacific Islander. This component explains the variation in the population that does not self-identify within the prescribed choices set by the Census Bureau (US Census Bureau, 2017b) (Fig. 3C). The fourth component explained 5.65% of the variance with the dominant variables being renter-occupied housing units and white households in renter-occupied housing (Fig. 3D). The fifth component that explained 4.13% of the variance was population living in group quarters. This component explains the variation in the population that does not reside in traditional housing units (e g. house, apartment, a mobile home or trailer), but instead occupy institutional (e g. nursing homes, mental hospitals or wards, hospitals, or prisons) and or non-institutional (e g. colleges, universities, military barracks, group homes, or shelters) (US Census Bureau, 2017b). To a lesser extent, the fifth component was also total male population. Block groups with larger male populations tend to have group quarters such as military and prisons. Component six explained 3.65% and component seven explained 2.91% of the variance and both were related to household size and number of dependents (Fig. 3E). While component six was Native Hawaiian and Other Pacific Islander, component seven related to those who identify as Black or African American. Component seven had an additional indicator of the age of dependents under 18 and over 65 years old, thus highlighting the sub-group of Black or African American households with some of the most vulnerable people. The eighth component explained 2.41% of the variance and related to age, with dominant variables loading highly on median age, households 65 years and older and those 75 years and over. This component also had median age of white females. The ninth component explains 2.16% of the variance and can be related to household size, for households with people who are over 18 years and white. The tenth component explained 1.95% and was family size of those who self-identify as some other race. The eleventh component was 1.77% and related the population who self-identify as American Indian and Native Alaskan. The final component accounted for 1.64% of the variation and related to family/household size for those who self-identify as Asian.

The block-groups with large positive z-score values indicate where the component loaded highly, and inversely areas with large negative z-scores indicate where there is a weak loading for that component. The 12 components identified in this study were comparable to studies conducted at similar spatial extent and geographic unit of analysis (Dunning and Durden, 2013; Hardy and Hauer, 2018; Rygel et al., 2006; Tate et al., 2010). The block-group z-scores for each of the 12 components of social vulnerability were mapped to analyze relationships between and among the components and compare their respective spatial distribution patterns. The first five components are shown in Fig. 3 below.

To identify the spatial distribution of social vulnerability and the potential loss associated with a hazardous flooding event in coastal North Carolina that the various population groups identified would withstand, the final social index was mapped in a spatially-explicit manner to illustrate the spatial distribution of areas of very high to low social vulnerability (Fig. 4). Of the total 236 block-groups that were included in the medium high to very high social vulnerability class (> 0.50 standard deviations), the Eastern Carolina COG region had the most (129), followed by the Cape Fear region with the second most vulnerable block-groups (55). The extensive distribution of highly socially vulnerable block-groups is near the cities of Goldsboro and Jacksonville, with Camp Lejeune, a very large military installation (group quarters) highlighted as very high social vulnerability (> 2.5SD). The areas highlighted as very high social vulnerability near New Bern and the city of Wilmington are dominated by elderly people living in retirement communities. There is also a pattern of high social vulnerability throughout the inland rural counties of Duplin, Greene, Wayne, and Lenoir that are dominated primarily by agriculture, larger family sizes and some predominantly non-white. There are 280 block groups falling within the low social vulnerability class (< −0.50 standard deviations) with 90 of them (32%) within the Cape Fear region. This region is made up of four counties (Brunswick, Columbus, New Hanover, and Pender), of which three are coastal, and New

Table 3
Summary of the social vulnerability components based on the results of the Principal Component Analysis (PCA).

Component Number	Component Name (and variables)	% Variance Explained	Cumulative %
1	Family Structure (white households household size, family size, children < 18 yrs old)	14.15	14.15
2	Population and Housing (number of occupied housing units, occupied housing units with white household, total population, number of races tallied, number of families)	9.84	23.99
3	Population by Race (some other race)	6.32	30.31
4	Housing (Renter-occupied housing and white households in renter-occupied housing)	5.65	35.96
5	Special Needs and Male Population (living in group quarters)	4.13	40.09
6	Family Structure and Race (household size and Native Hawaiian and Other Pacific Islander households)	3.65	43.74
7	Race and Family Structure (Black or African American households and number of dependents aged < 18 or > 65)	2.91	46.65
8	Age and Race (65 or older and white)	2.41	49.05
9	Household Size (age 18 or older and white females)	2.16	51.21
10	Family Size ("Some Other Race")	1.95	53.16
11	Population by Race (American Indian or Native Alaskan)	1.77	54.93
12	Family/Household Size (Asian)	1.64	56.57

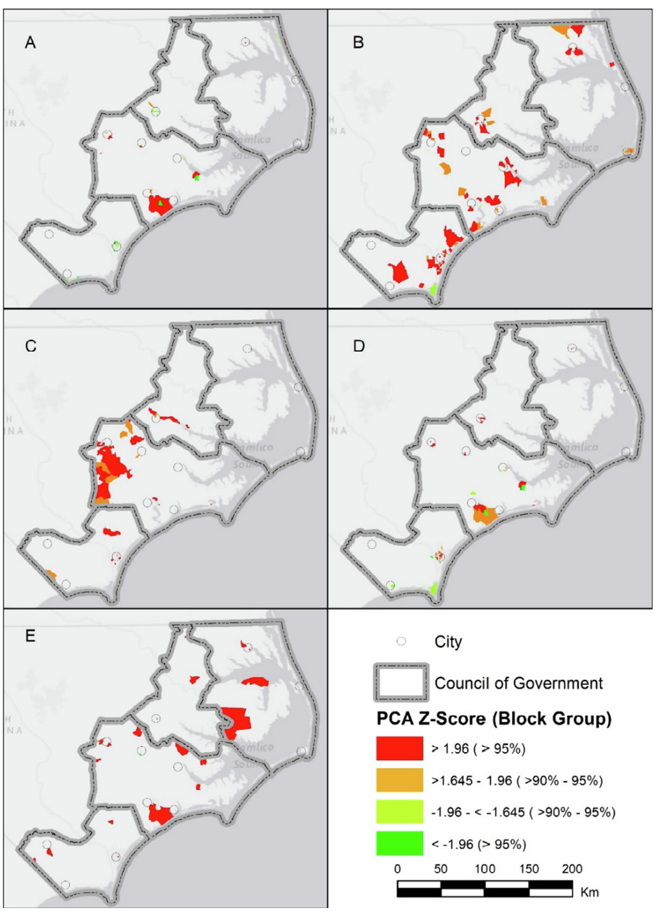

Fig. 3. The spatial distribution of the first five PCA components by-group z-score with the data displayed using standard deviations at the 95% and 90% confidence intervals. A: family structure (white head of household and > 4 children), B: total population and total housing units, C: non-white race, D: renter-occupied housing; and E: household size and number of dependents.

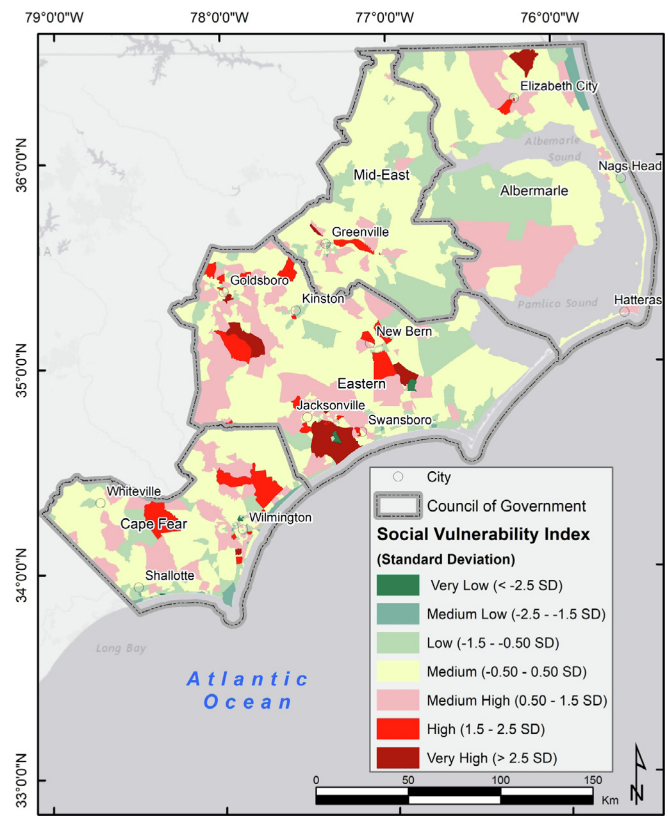

Fig. 4. Spatial distribution of the final weighted social vulnerability index for 1013 block-groups within the study area.

Hanover County which has the highest total population (202,667 people) in the study area.

To determine if there is statistical significance in the spatial distribution of social vulnerability, a spatial autocorrelation was performed using the index values for all block-groups. The results demonstrated a significantly clustered spatial distribution at both local (z-score = 23.96) and regional distance (z-score = 18.49) band thresholds (25 and 91 km), respectively. This supports the visual interpretation that there is a significant clustering of block-groups with similar social index values. Further analysis using a Local Anselin Moran's I test identified where areas of a high and low social vulnerability values cluster or exist as outliers when spatially compared to the neighboring block-groups at two distance band thresholds (25 and 91 km respectively) identified as critical for the analysis based on the Ripley's K statistic. This analysis step identified block-groups with similar social index values that are significantly clustered, potentially indicating the existence of larger population groups susceptible to loss within a community that may extend beyond the borders of a regional governing body. There is a distinct area of significant clustering of high social index values at the regional distance band throughout the Eastern Carolina region, centered on the Jacksonville, Goldsboro and New Bern municipalities, with additional significant clustering in the rural areas outside these municipalities (Fig. 5). When a local distance threshold is applied to the study area there is a loss in the significant clustering of low social index values in the upper Albemarle region of the study area

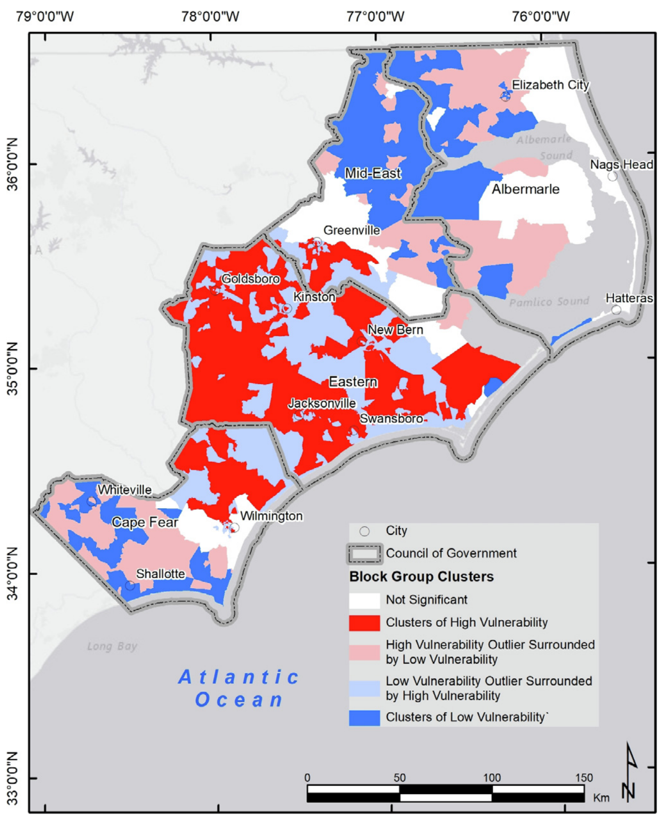

Fig. 5. Results of the Local Anselin Moran's I test for social vulnerability clusters and outliers at the regional distance band (91 km).

and the appearance of a significant clustering of high values in the Cape Fear region when a greater weight is placed on those features at a shorter distance.

3.2. Physical vulnerability

We next identified the block-group level of exposure to inundation resulting from the proportion of 100-year floodplain and proportion of structures exposed to potential damage that intersect the 100-year floodplain in North Carolina's 28 coastal counties. In the study area, 924 (91%) of the total 1013 block-groups in the study area intersect the 100-year floodplain (Fig. 6). This finding identifies the significant area and populations that are continually at a high level of exposure to potential adverse impacts from 100-year flood events that coastal North Carolina has frequently experienced, especially in the last decade. Within the block-groups intersecting the 100-year floodplain, a total of 128,441 buildings cross the special flood hazard area and, of those, 58,281 (45.3%) buildings are exposed to damage from the modeled BFE of a 100-year flood event (Fig. 6). Of the 45.3% of the buildings directly exposed to damage based on their finished-floor elevation relative to BFE, 25.9% are only elevated above the base flood level by one foot, while the rest (74.1%) fall below the level of elevation that would protect them from withstanding structural damage during a flood event (Fig. 7). As shown by Rogers et al. (2011), materials built into the subfloor (e.g. insulation, duct work, and/or electrical) of a structure will begin to experience damage from inundation when floodwaters reach one foot below the FFE. Close to 15% of all existing buildings in coastal NC currently sit 4 ft or more below the level of BFE in their designated flood hazard zone, making these structures directly vulnerable in the case of a 100-year flood event or worse.

To identify the spatial distribution of where areas of greatest physical vulnerability to potential damage from inundation exist in coastal North Carolina, the final standardized physical index was mapped using

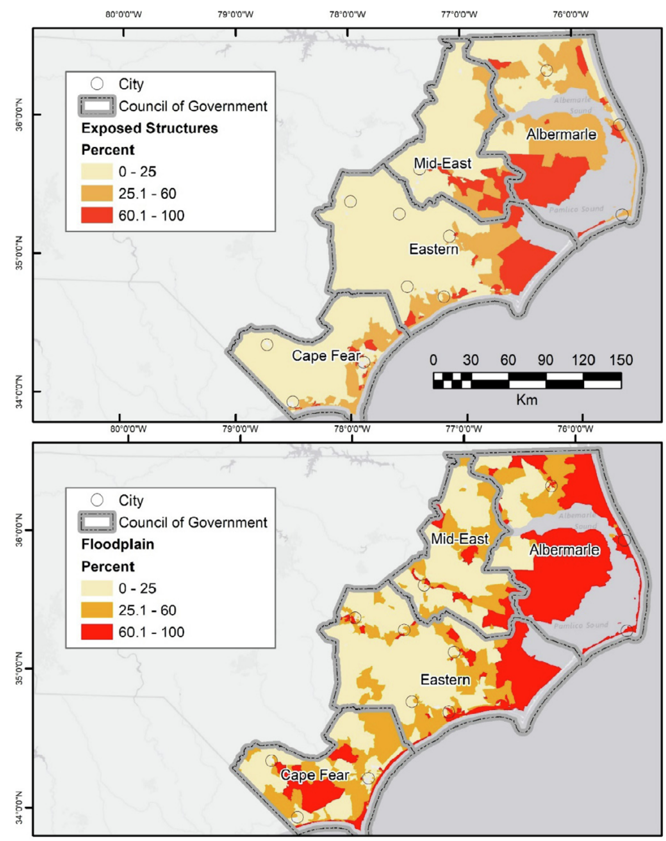

Fig. 6. Spatial distribution of the proportion of physically exposed structures (top) and proportion of 100-year floodplain area (bottom) at the block-group level of geography.

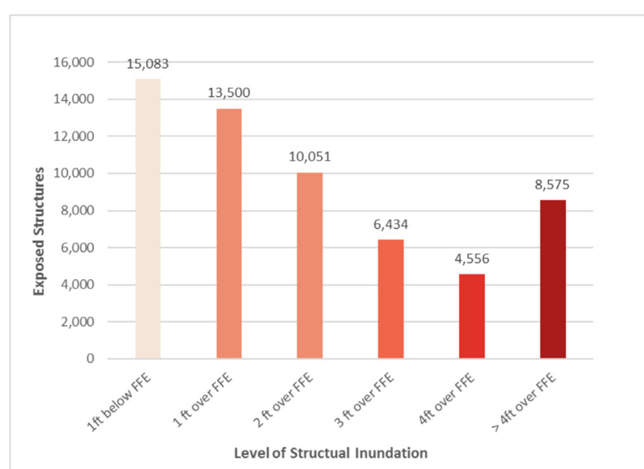

Fig. 7. Summary of the structures determined to be physically exposed to inundation. The data is summarized based on the difference between the finished-floor elevation (FFE) and the base flood elevation (BFE).

standard deviation class intervals (very high, high, medium high, medium and low) (Fig. 8). Of the 924 block-groups, 440 (48%) were low vulnerability (< 0.5 standard deviation) and 251 (27%) were high vulnerability (> 0.5 standard deviation). The high vulnerability block groups were located along the coast with the most in Eastern Carolina (91), then Cape Fear (68) and Albermarle (65), and the least in Mid-East (27 There were 101 block-groups with very high vulnerability (> 1.5 standard deviation) and these were located in Eastern (40), Albermarle (26), Cape Fear (24), and Mid-East (11). The results show

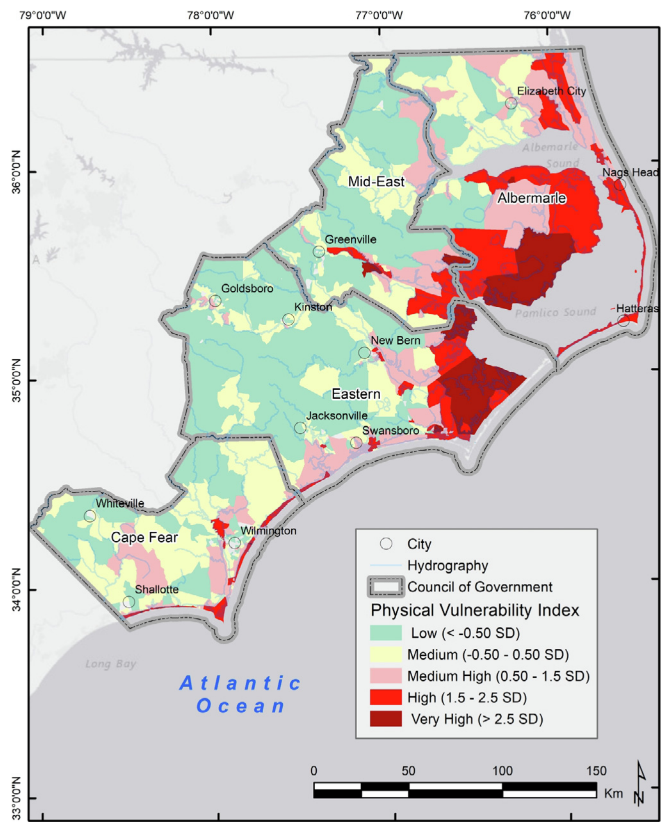

Fig. 8. Spatial distribution of the physical vulnerability index.

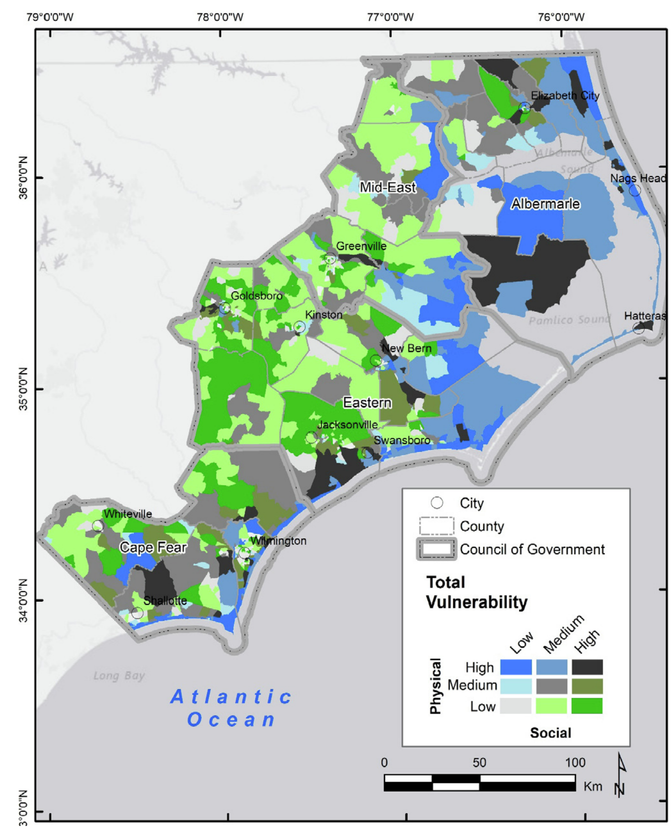

Fig. 9. Spatial distribution of block-groups with high physical vulnerability and high weighted social vulnerability index values.

that the physical exposure to inundation decreases as we move inland away from the coastline and is also highest along the Pamlico and Albermarle inner shoreline which is an area dominated by low-lying and flat terrain. There is a distinct pattern of higher exposure along the major estuaries and inland waterways following the extents of the 100-year floodplain delineations.

3.3. Integrated population vulnerability to inundation in coastal North Carolina

The composite vulnerability index was mapped to identify the spatial distribution of the combined effects of social and physical vulnerability throughout coastal North Carolina. The vulnerability to inundation index was mapped using standard deviations with special attention given to identifying areas of high (> 0.50 standard deviation), medium (−0.50–0.50 standard deviation), and low (< −0.50 standard deviation) vulnerability (Fig. 9 and Table 5). The location of both high physical and social vulnerability (shown in black in Fig. 9) is along the coast and inland areas and is only 4% of the study area. An interesting finding is that 27% of all block-groups in our study area (28 coastal counties) are classified as high physical vulnerability with 24% of block-groups falling in the high social vulnerability class (Table 4). A more nuanced summary of block-group level vulnerability identifies the Eastern Carolina region with the highest number (14) of block groups with the highest combined vulnerability, but the sizes of the COGs are not equal (Table 5). Therefore, the percentage of block groups with the highest vulnerability was in the Albermarle COG with 12 block groups (11%). The most spatially dominant result was that the Albermarle COG had 41 block groups (37%) with high physical vulnerability and medium social vulnerability. Conversely, the three other COGs (Cape Fear, Eastern, and Mid-East) were all dominated by low physical and medium social vulnerability (23%, 28%, and 44%, respectively). Lastly, the Cape Fear COG was also dominated by high physical and low social vulnerability (20%) and medium physical and social vulnerability (20%) and the Eastern COG was dominated by low physical and high social vulnerability (23%). The results identified some urban areas that are particularly vulnerable both in terms of their physical exposure and socially: Elizabeth City, Hatteras, Nags Head, Greenville, New Bern, Goldsboro, suburban Wilmington and the coastal towns of Wrightsville and Carolina Beach.

The pre-aggregation of the indices identified distinct spatial patterns of physical vulnerability concentration along the coastline and significant clustering of high social vulnerability index values in the inland Eastern Carolina region. The final aggregated vulnerability to inundation index was tested for spatial autocorrelation. The block-groups were significantly clustered at both the local (25 km) (z-score = 6.47) and regional (91 km) (z-score = 9.63) distance band thresholds established using the Ripley's K statistic. A cluster analysis (using Anselin Local Moran's I) showed a clear clustering of high vulnerability to inundation index along the coast and low vulnerability inland (Fig. 10). As distance away from the coastline increases, significant clustering of low index values border the western boundary of the study area, but throughout this region there are many outliers of high index values of block-groups appearing at significant distance away from the highly physically exposed coastline.

4. Discussion

This integrated approach to identifying areas of high vulnerability to an exposure (in this case inundation, as modeled by the National Flood Hazard Maps) that takes into account in a spatially-explicit manner both social sensitivities and physical exposure at the block-group level within coastal North Carolina, provides valuable insight into the benefits of conducting sub-county analyses of a population's vulnerability to inundation. The results from the individual social and physical assessments, respectively, provide an essential understanding for future management of what contributes to the vulnerability within

Table 4
Frequency correlation results for the intersection of physical and weighted social vulnerability index values for block-groups in the 28 coastal North Carolina counties.

Frequency/Percent		Physical Vulnerability			
		Low	Medium	High	Total
Weighted Social Vulnerability	Low	85/9.20%	55/5.95%	107/11.58%	**247/26.73%**
	Medium	224/24.24%	124/13.42%	106/11.47%	**454/49.13%**
	High	131/47.62%	54/5.84%	38/4.11%	**223/24.13%**
	Total	**440/47.62%**	**233/25.22%**	**251/27.16%**	**924/100%**

each of these systems separately. Moreover, the integrated vulnerability to flooding measure provides insight into how these two systems interact to increase and or decrease a population's vulnerability to inundation in low-lying, coastal areas that are projected to be subject to increasingly intense and more variable precipitation and extreme events (Carter et al., 2018). Based on our analysis that considered, equally, over 1000 social-demographic characteristics in an unbiased PCA, we isolated 12 major social characteristics (Table 3) contributing to the increase in a community's vulnerability to loss. Our results are comparable to findings from studies conducted at similar spatial scales of analysis that highlight that socio-demographic characteristics such as family structure, population by race, housing conditions (owner vs. renter-occupied housing primarily), special needs populations, and household and family size play an overwhelmingly important role in determining community vulnerability from a social perspective (Dunning and Durden, 2013; Hardy and Hauer, 2018; Rygel et al., 2006; Tate et al., 2010). The significant finding from our physical analysis found that presently 45% of the structures within the 100-year floodplain are now exposed to potential damage and that 90% of the coastal area of interest intersects the most severe areas of modeled inundation, the 100-year floodplain. By combining potential building damage and social characteristics that contribute to or may heighten potential loss resulting from an inundation event, we were able to not only identify what is at risk, which is a limitation of many hazard studies, but, more importantly, who is vulnerable and where those vulnerable pockets of the population are.

An essential aspect of the quantification of the social vulnerability is the capturing of a significant portion of the variation that exists within the area of interest within the fewest number of components. The amount of variation captured in this study (56%) is low when compared to other studies, that tend to capture higher percent variation (70–80%) in fewer components (Cutter et al., 2003; Dunning and Durden, 2013; Hardy and Hauer, 2018; Rygel et al., 2006; Tate et al., 2010). The small amount of variation captured in this study is a result of the inclusion of a broad set of variables (492) used in the principal component analysis. Similar studies that used a subjective selection of variables (e.g. < 42) in their principal component analysis were better able to explain the

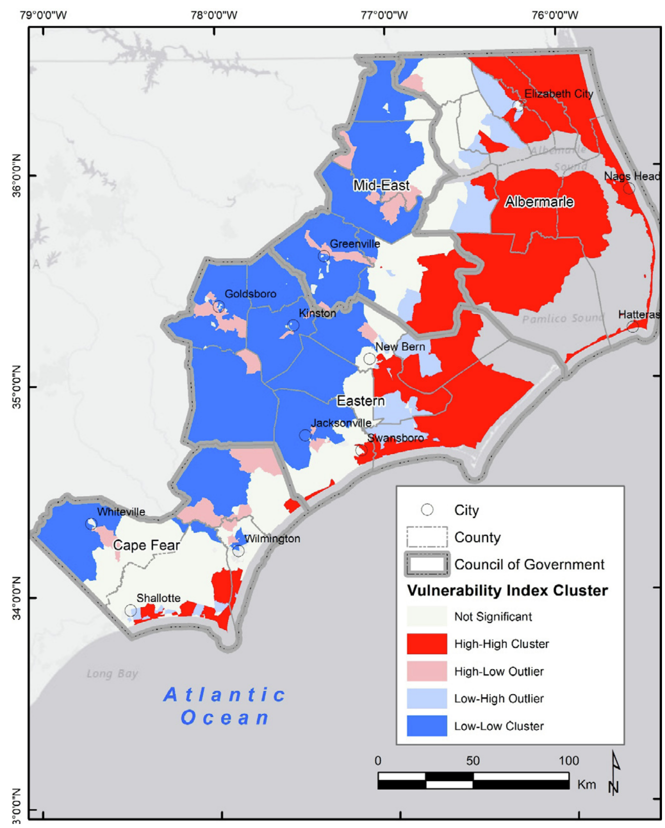

Fig. 10. Results of the Local Anselin Moran's I test for the integrated vulnerability clusters and outliers at the regional distance band (91 km).

variation that exists in their study area, but their designs are susceptible to biased choices in variable inclusion and can thus result in potentially skewing the results (Jones and Andrey, 2007). One limitation of our social vulnerability model as presented in this paper is the fact that we

Table 5
Summary of the number and proportion of each COG with high physical and high social block-groups (H-H) summarized by county and regional council of government.

Vulnerability	Albermarle		Cape Fear		Eastern		Mid-East	
(Physical-Social Combined)	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion
H-H	12	0.107	9	0.040	14	0.040	3	0.020
H-M	41	0.366	15	0.067	38	0.108	12	0.079
M-H	3	0.027	22	0.098	25	0.071	4	0.026
H-L	12	0.107	44	0.196	39	0.111	12	0.079
L-H	7	0.063	22	0.098	82	0.234	20	0.132
M-M	20	0.179	45	0.200	37	0.105	22	0.146
L-M	8	0.071	52	0.231	98	0.279	66	0.437
M-L	9	0.080	16	0.071	18	0.051	12	0.079
L-L	8	0.071	20	0.089	32	0.091	25	0.166
Total	**112**	**1.000**	**225**	**1.000**	**351**	**1.000**	**151**	**1.000**

did not include income into the calculation of the social vulnerability index due to the fact that the American Community Survey data containing income is not decennial and would thus not correspond temporally with all other census variables analyzed in this study. Another limitation is the lack of inclusion of property value or rental values explicitly in the calculation of the social vulnerability index due to the spatial mismatch of the land tax information and our unit of analysis. For future analyses, the inclusion of a greater diversity of variables could potentially lead to capturing a greater understanding of the variation that contributes to the increase in social vulnerability while not selectively limiting or omitting variables.

Within the four regional governing bodies considered in our study, the Eastern Carolina Council of Government has the largest total population with also the most significant number of block-groups at both the high and extreme high-high index values across all three of the indices of vulnerability. Examination of the spatial distribution of the highly vulnerable block-groups supports our hypothesis that vulnerability is concentrated primarily in the coastal counties (Fig. 9), which is comparable to similar studies (Tate et al., 2010b). However, our findings also show that there are areas located at a greater distance away from the coast that do display high levels of vulnerability to inundation that were unexpected. While current coastal management heavily favors areas of high physical exposure in mitigation decisions, the identifications of these areas may influence future planning, mitigation or adaptation efforts in the regions that were once not considered to be at risk of adverse effects from a potential inundation hazard.

The opportunity to analyze the FFE of structures within the 100-year floodplain and create a direct measure of the portion of buildings exposed to damage under the currently modeled BFE is a unique given that digital data at this scale is only available within the state of North Carolina at the present moment. Of the approximately 900,000 structures within our study area, we are limited to analyzing the intersection of only 128,441 of those due to the lack of modeled BFE for regions outside of the 100-year floodplain. The constraint of NFIP base flood predictions not modeled for areas within the 500-year floodplain, which in the past two decades has experienced record levels of inundation from Hurricane Florence (2018), Matthew (2016) and Floyd (1999) in North Carolina alone, limits the ability of state-level floodplain managers to accurately assess the exposure of the housing infrastructure to future flooding. The modeling of base floods for areas beyond the 100-year floodplain within the NFIP would provide the ability analyze exposure to inundation in regions that until recently were once not considered to be at risk as evidenced by our analysis. One of the limitations of our work is that while the physical vulnerability measure accounts only for the floodplain in its calculation, we do consider storm-water runoff in our physical vulnerability calculations. Future work will incorporate derivation of actual flooding extents following major storms event (such as Matthew or Florence) and thus a more direct accounting of how well our model is performing when compared with actual flooding extents post-storm, as well as additional socio-economic variables such as income, property or rental values. We recommend that other coastal states invest in obtaining high-resolution finished floor elevation datasets to enhance their ability to plan for and mitigate for coastal and inland inundation in the coming decades.

5. Conclusions

The Fourth National Climate Assessment identified storm-related coastal and pluvial inland inundation as major risk factors the US Southeast will be increasingly facing in the coming decades in their planning efforts and strongly encourages municipalities start engaging in adaptation planning (Carter et al., 2018). In this context, we presented a first-of-its-kind analysis of social and physical vulnerability to coastal inundation using the highest level of census geography available (block-group) and unparalleled high-resolution, individual building footprints with finished-floor elevations currently available for the entire state of North Carolina. Our statistical analyses using PCA on hundreds of variables from 228 Census tables identified important social factors and these factors are similar to previous research (Dunning and Cutter and Scott, 2000) and highlighted groups with heighted social vulnerability that must be better accounted for in planning and adaptation efforts. Secondly, computing social vulnerability at the block group level of geography contributed greatly to the identification of vulnerability because this higher level of spatial resolution provides more detail to be compared with floodplain vulnerability that cannot be obtained using census tract or county level of geography. With the higher resolution block group level of geography, multiple levels of levels of governance can be involved in the investigation of adaptation strategies, at sub-county scale. The block group level of analysis provides information that can be further generalized, or aggregated, to lower spatial resolutions, allowing for assessments by municipalities, towns or sub-divisions. The scale of the analyses conducted in this paper improves the usefulness of vulnerability modeling results in future coastal planning and management efforts aimed at decreasing vulnerability to inundation throughout coastal North Carolina within scales ranging from the community to transboundary governing bodies.

Investigating building footprint, finished floor elevation, and age of structure enables vulnerability assessment at the parcel level and accounts for changes in building codes through time; a type of analysis previously not possible to conduct. Additionally, as communities and counties apply to FEMA to be included in the Community Rating System, it is imperative to know that our modeling approach is transferable to other coastal regions where highly resolved data on building locations and the elevation of those buildings above ground are available and we show that incorporating such data can help make modeling and assessment efforts more usable at finer scales relevant to management and governance levels.

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